Domain Bias in Web Search

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ABSTRACT

This paper uncovers a new phenomenon in web search that we call *domain bias* — a user's propensity to believe that a page is more relevant just because it comes from a particular domain. We provide evidence of the existence of domain bias in click activity as well as in human judgments via a comprehensive collection of experiments. We begin by studying the difference between domains that a search engine surfaces and that users click. Surprisingly, we find that despite changes in the overall distribution of surfaced domains, there has not been a comparable shift in the distribution of clicked domains. Users seem to have learned the landscape of the internet and their click behavior has thus become more predictable over time. Next, we run a blind domain test, akin to a Pepsi/Coke taste test, to determine whether domains can shift a user's opinion of which page is more relevant. We find that domains can actually flip a user's preference about 25% of the time. Finally, we demonstrate the existence of systematic domain preferences, even after factoring out confounding issues such as position bias and relevance, two factors that have been used extensively in past work to explain user behavior. The existence of domain bias has numerous consequences including, for example, the importance of discounting click activity from reputable domains.

Categories and Subject Descriptors

H.1 [**Information Systems**]: Models and Principles

General Terms

Experimentation, Human factors, Measurement

Keywords

domain bias, user behavior, web search

1. INTRODUCTION

Obtaining high quality labeled data is important for a search engine since it can be used both for creating a better ranking function, as well as assessing the quality of search results. Human judgments are commonly used for both purposes. However, over time it has become evident that human judgments will not scale. Specifically, obtaining human judgments for every country/language as well as specific verticals such as commerce and health will be challenging in terms of cost and efficiency.

As a result, the click logs have been proposed as a substitute for human judgments. Clicks are a relatively free, implicit source of user feedback. Finding the right way to exploit clicks is crucial to designing an improved search engine.

However, clicks are fraught with biases. The most widely studied bias is position bias [12, 13], a user's propensity to click on a search result just because it appears closer to the top of a search results page. Much work has been invested in both establishing the existence of position bias [8, 18], as well as understanding how to remove position bias from click activity [2, 3, 7]. Other biases are also known to exist, for example, snippet attractiveness bias, a user's propensity to click on a result because the query terms appear in bold in the title multiple times [23].

In this paper, we uncover a new phenomenon in click activity that we call *domain bias*—a user's propensity to click on a search result because it comes from a reputable domain, as well as their disinclination to click on a result from a domain of unknown or distrustful reputation. The propensity constitutes a bias as it cannot be explained by relevance or positioning of search results.

Our goal is to provide incontrovertible proof of the existence of domain bias. We do so via a series of carefully designed experiments. We ask if a search engine drastically changes the surfaced domains, do domain clicks also change accordingly? Amazingly, the answer turns out to be no. Instead, we find that users click on the same domains despite changes in surfaced content. In a similar vein, if we take two search engines of wildly different relevance, we ask if domain clicks also swing wildly. Again, to our surprise, the answer is no. We observe that the top domains garner a larger and larger fraction of the clicks and it is not because search engines are surfacing a smaller number of domains. On the contrary, search engines are changing the domains they show. It is users who have decided to visit a smaller number of domains.

It should not be surprising that users have learned to trust some domains over others. Indeed, past work such as TrustRank measures user trust at a domain level [10]. A recent eye-tracking study also confirms that users pay at-

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tention to the displayed URL[1]. One could argue that search engines already know this and exploit it by using the PageRank of a domain in their scoring functions so as to boost documents from domains of high reputation.

What is surprising is that users click on results from reputable domains even when more relevant search results are available. Our experiments are geared towards proving that domains can so drastically influence perceived relevance that users will favor some domains, regardless of content. Viewing content on the Internet as products, domains have emerged as brands. And users have developed such fierce brand loyalty that their clicks are tainted by domains.

We establish the existence of domain bias via a Pepsi/Coke style blind taste test. In our experiment, we request relevance feedback from different users where each is shown a query and two search results in three scenarios: with the snippet only (i.e., absent domain), with the snippet and true URL, and with the snippet and swapped URL. We find that in 25% of the cases, the behavior of users resembles a blind following to domains. For example, for the query {one of the most common types of heart disease}, there are two snippets and two domains, one from `webmd.com` and another from `genetichealth.com`. Absent domain, users prefer the snippet from `genetichealth`. When domains are revealed, users prefer the snippet of `webmd`. More interestingly, when we paired the `genetichealth` snippet with the `webmd` URL, users flip their preference and go back to preferring the snippet from `genetichealth` (now paired with the domain `webmd`). The experiment demonstrates that users have become reliant on domains in assessing the relevance of search results, and may in some cases blindly trust content from reputable domains.

Next, we design an experiment to demonstrate a systematic bias towards certain domains that spans across search queries. Designing an experiment to tease out the existence of domain trust is a non-trivial task. One confounding factor is relevance—perhaps the reason why certain domains attract the majority of clicks is that content from the domain appears to be more relevant to the user. Another confounding factor is position bias—perhaps the search engine tends to rank some domains higher than others and that is what leads to the observed domain preference. We design an experiment that removes the relevance factor by focusing on query, URL1, URL2 combinations that are labeled equally relevant by a strong majority of a panel of human judges. Further, the experiment removes position bias by only drawing inferences about domain A being preferred to domain B when A is ranked below B and yet still A is clicked more often. By accumulating these preferences, we find that we can construct an ordering of domains that agrees well with user preferences. Such an ordering with strong agreement would have been impossible in the absence of domain trust, thus confirming its presence.

The existence of domain trust has important consequences for several areas of web search research. For example, it influences the design of user click models [3, 6, 7, 9], which have focused on relevance and position of the search results as the principal factors that influence user clicks. Domain bias introduces a new factor that needs to be considered. It also influences the large body of literature of learning relevance from clicks. While many studies have considered ways to remove position bias [2, 7, 11], we must now consider how to remove domain bias. Domain bias also affects how queries are categorized as navigational vs. informational. As user visits concentrate on fewer domains, former informational queries may now appear navigational, and semantic approaches may be needed to distinguish between the two types.

The goal of this paper is to provide indisputable proof of the existence of domain bias. We believe this is an important phenomenon and we take careful steps in establishing that it exists beyond reasonable doubt. We also take first steps in quantifying the amount of bias as it can help with the aforementioned applications. Nonetheless, our approach is limited in scale due to the reliance of human labels. The quantification of domain bias at web scale remains a deep challenge and we leave it as a great question for future work.

2. RELATED WORK

The bias of user clicks on search engines has been studied before. Joachims *et. al.* found user clicks to be good signals for implicit relevance judgments but observed via an eye-tracking study that there is considerable position bias [12]. Later, Craswell *et. al.* carried out ranking perturbation experiments and proposed a cascade model: users scan results from top to bottom and make click decisions based on relevance [6]. Similar to our study, Craswell *et. al.* found that users did not blindly trust search engines. Unlike the study by Craswell *et. al.*, however, our findings are at the aggregate level of page domains and explain clicks beyond pure relevance. In [23], the authors show that users are biased towards “attractively” formatted snippets. Our experiments are geared towards establishing a different bias, by pairing snippets with swapped URLs.

User browsing models for search engine results, both organic and sponsored, have attracted considerable attention in recent years [1, 3, 6, 9, 21, 22, 23]. These models aim to estimate the click-through rate (CTR) of a result (i.e., the probability that a result is clicked), given the result's position and previous clicks in the user session. The CTR is commonly modeled as the product of the examination probability and the perceived relevance of the result (probability of a click given examination). The models vary in the examination probability and perceived relevance functions, but all agree that these functions depend only on the current state of the results (i.e., pages) and the current user's session clicks. On the other hand, our work shows that CTR is not only influenced by relevance and examination but also by domain preference.

It is well known that page quality is correlated with its hosting domain. There is related work on domain trust in the context of spam. For example, Gyöngyi *et. al.* proposed TrustRank – PageRank like ranking of domains based on a seed set of trusted reputable sites [10]. It is common practice for search engines to use domain as a feature in ranking. For example, PageRank [17] can be applied to the hyperlink structure on domains to obtain domain rank scores. Alternatively, domains that garner many clicks may be boosted higher in the ranking. Our work shows that if clicks are used to boost pages in the ranking, that domain bias must first be discounted.

A related line of research is on the bias of search engines on page popularity. Cho and Roy observed that search engines

[1] “Eye-tracking studies: More than meets the eye”, published at `http://googleblog.blogspot.com/2009/02/eye-tracking-studies-more-than-meets.html`, 2009.

penalized newly created pages by giving higher ranking to the current popular pages [4]. A number of solutions were proposed including using the change in popularity as a signal of page quality [5] and partial randomization of ranking [19]. Although this line of work is related to ours in that we look at the influence of search engines on users, our focus is different: we aim to understand and model user's long-term preference for specific domains.

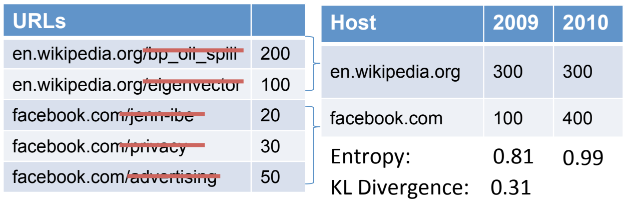
There are a number of macro-level user behavior studies that we will present in Section 3. For example, [20, 14, 15] analyze user traffic from search engines to individual sites and characterize search and browsing behavior. Unlike previous studies that characterize search behavior at a particular time point, our work emphasizes longitudinal search behavior. Mei and Church [15] conducted a related study where they showed that the visited web at a particular point in time has low entropy. Our work is different in that we look at the visited web over time. We similarly confirm that user visits are predictable, but we also point out that user visits are slow to change. Users are consistent about the domains they visit and are less influenced by changes in the displayed results.

3. SEARCH ENGINE INFLUENCE

We set out to study user domain bias by examining user behavior from search engines at the aggregate level. Our goal is to check whether users simply follow search engines and click on the top returned results without giving them much scrutiny. So we start by comparing the changes in the top displayed results to the changes in the clicked results. Intuitively, if users have little preference for domains, we expect the changes in the displayed results to trigger equivalent changes in the clicked results. Surprisingly, however, in spite of the changes in the displayed results we find that clicks tend to be rather stable with respect to domains.

Our experiments also reveal that search results concentrate over time on fewer domains with increasingly larger share of results pointing to the top domains. This trend is accompanied by an increase in click-through rates (even after factoring out query distribution changes) and is in contrast to the growing size of the web content and the number of registered domains.

Although the evidence we present in this section alone does not definitively prove the existence of domain bias (we provide more rigorous experiments in the subsequent sections), the results are likely to be potential consequences of the phenomenon. By pointing out the potential consequences up front, we motivate careful examination of domain bias in web search.



URLs	
en.wikipedia.org~~/bp_oil_spill~~	200
en.wikipedia.org~~/eigenvector~~	100
facebook.com~~/jenn-ibe~~	20
facebook.com~~/privacy~~	30
facebook.com~~/advertising~~	50

Host	2009	2010
en.wikipedia.org	300	300
facebook.com	100	400
Entropy:	0.81	0.99
KL Divergence:	0.31	

Figure 1: Methodology.

Why Domains? We study user visit patterns in terms of the aggregate distribution of page views over their hosting domains. Although technically we aggregate at the level of hosts, we use the term "domains" throughout the paper. Consider Figure 1. This is a sample of URLs clicked by search engine users with the total number of clicks each URL received, irrespective of queries. We aggregate clicks on pages from the same host to obtain a distribution of clicks over the host names. We look at hosts and not the individual pages because studying visits with respect to pages over a long time period becomes impractical: after one year nearly 60% of the pages are replaced by new ones [16]. More importantly, aggregating visits over hosts makes sense because hosts roughly correspond to individual publishers on the web, e.g., each sub-domain of `wordpress.com` corresponds to an individual blog. We also performed experiments on top level domains and obtained similar results to the ones presented here.

Data. Our findings are based on data derived from search logs. We study user visit patterns over a seven-day period at two different time points: July 2009 and July 2010. Looking at the same period in 2009 and 2010 minimizes the temporal bias. To remove variance due to geographic and linguistic differences in search behavior, we only consider queries issued in the English speaking United States locale.

Method. We use Shannon entropy to measure the display and visit distribution of domains. Compared to other measures such as power-law exponent, Shannon entropy has an intuitive meaning: it is the average number of bits required to encode the destination domain of each visit. Increasing entropy is a sign of user visits becoming more diverse, while decreasing entropy is a sign of user visits becoming more predictable and suggests the formation of domain preferences.

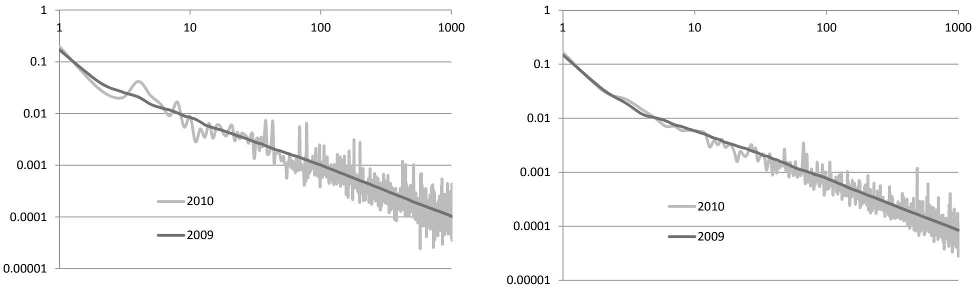
We use KL(Kullback-Leibler) divergence to measure the difference between two distributions. Recall that KL divergence is defined as $D_{KL}(p||q) = \sum_{d \in \mathcal{D}} p(d) \log \frac{p(d)}{q(d)}$ for two distributions $p = \{p(d)\}$ and $q = \{q(d)\}$. KL divergence measures the average number of extra bits required to encode the distribution of p using the optimal encoding of q. Together with Shannon entropy, it provides an intuition of the magnitude of distribution changes. One problem with the use of KL divergence is that it is undefined when there is a domain d such that $p(d) > 0$ and $q(d) = 0$. To address this issue, we employ the standard add-one smoothing: before computing the distribution, we add one to the count of each domain.

3.1 Displayed vs. Clicked Results

We compare the search displays and user visits from the same search engine in two time periods: July 2009 and July 2010. We refer to these data sets as 2009 and 2010 data, respectively. We only consider the top 5 results returned by the search engine for each query. By focusing on the top results, we aim to reduce the influence of examination bias: users scan results from the top to bottom, so the top results are more likely to be examined [12]. We also analyzed the top 1 result and top 10 result distributions and found similar insights to the ones we present here.

Table 1 shows the ten most frequently displayed domains in 2009. We show the display and visit shares[2] point-wise for each domain in 2009 and 2010. Observe the drastic change

[2] The display (visit) share of a domain is the number of times the domain is displayed (visited) over the total number of displays (visits).



(a) Display Distribution Changes

(b) Click Distribution Changes

Figure 2: Display and click distributions point-wise for 2009 and 2010. Both (a) and (b) plots are on log-log scale. The points are connected in a line for better exhibition of the distribution differences.

Domains	2009 display	2010 display	2009 visit	2010 visit
`en.wikipedia.org`	0.0750	0.0923	0.0274	0.0279
`www.facebook.com`	0.0119	0.0251	0.0233	0.0497
`www.youtube.com`	0.0098	0.0104	0.0177	0.0197
`www.google.com`	0.0085	0.0087	0.0276	0.0236
`groups.google.com`	0.0053	0.0002	0.0001	0.0001
`checkout.google.com`	0.0043	0.0000	0.0000	0.0000
`mail.yahoo.com`	0.0044	0.0030	0.0067	0.0069
`www.yahoo.com`	0.0044	0.0034	0.0137	0.0110
`www.imdb.com`	0.0042	0.0035	0.0038	0.0036
`blog.facebook.com`	0.0042	0.0001	0.0000	0.0000

Table 1: Display and visit share for a sample of domains in 2009 and 2010. The ten domains are the most displayed domains in 2009.

in the display shares in contrast to the more modest change in the visit shares. The entropy, as well as the KL divergence, of the distribution of displayed and visited domains are shown in Table 2.

	displays	visits
2009 entropy	15.24	15.07
2010 entropy	14.24	14.72
KL divergence	1.33	0.76

Table 2: Summary of the changes to the distribution of displayed and visited domains from 2009 to 2010.

From Table 2, we can see that while the distribution of displayed domains undergoes significant changes, there is no comparable shift in the distribution of visited domains. To provide a visual illustration of the scale of changes behind the numbers, we plot in Figure 2 (a) and (b) the distributions from the two time periods point-to-point for displayed and visited domains, respectively. In both figures, we use 2009 data as the baseline, sorting all domains in decreasing order of their frequencies in 2009. We then bin every 10 domains and plot the cumulative frequency for each bin as the dark curve. Since we order by the frequencies in 2009, the dark curve monotonically decreases. With the light curve, we plot the corresponding frequency for 2010 data, keeping the same binning of domains as for 2009. As a result, the curve need not be monotonic. This presentation allows one to visually observe the difference between the two distributions. From Figure 2(a) and (b), we can see that the displayed results have undergone a larger change compared to the visits. This effect is especially prominent in the head of the distributions. Furthermore, the discrepancy between the changes in the displays and the visits are prominent even when looking at the distributions for the top result only.

3.2 Nature of the Displayed Result Changes

We next look at the nature of the changes in the surfaced results between 2009 and 2010 (by the same search engine).

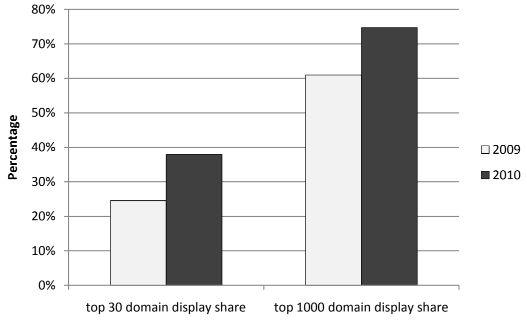


Figure 3: Cumulative share of displays attributed to the 30 and 1000 most popular domains in 2009 and 2010, respectively.

Figure 3 shows the cumulative share of search displays attributed to the 30 most popular domains in the time periods of July 2009 and July 2010. As seen from the graph, 2010 share of search results pointing to the top 30 domains increases from 25% to 38% and to the top 1000 domains from 61% to 74%. Note that the increase is not limited to particular few domains, e.g., `facebook.com`, but rather applies to a large set of domains beyond the topmost few. Further, the observed trend cannot be explained by the increasing share of navigational queries, as the increase in the share of search results pointing to the top 1000 domains persists after re-normalizing for the query distribution changes.

The shift of the search results towards popular domains is also demonstrated by the entropy of the distribution of search displays over domains in Table 2. There is a 1-bit drop in the entropy, which is quite drastic when viewed in the context of the vast growth of the web. While there is an increasing volume of content on the web and an increasing number of sites, search engine results tend to concentrate on increasingly fewer domains!

Both the increasing share of search displays attributed to the top domains and the drop in the overall entropy indicate that the search engines show increasingly less diverse domains. The logical question is whether this trend aligns with the user preferences. It turns out that the answer is yes: for the particular search engine we study, the click-through rate in 2010 compared to 2009 has increased dramatically; so does the click-through rate on the top position of search results. The trend can be verified even after re-normalizing for the query distribution changes, which may suggest (although not definitively yet) that increasing number of users develop preference for specific domains that cannot be explained by the increasing share of navigational queries alone.

3.3 Clicks of Different Search Engines

Our analysis has so far focused on a particular search engine. Next, we compare the distribution of clicks from two different search engines side by side observed in the same time period in July 2010. Search engine A is a major search engine with a large market share, while search engine B is a niche search engine with a tiny market share. Given differences in the two search engines' target audiences, we hypothesize a large difference in their displayed results (we verified this hypothesis with a limited sample of queries). If users have an intrinsic preference for specific domains, their clicks should be similar independently of the search engine they use and the results surfaced.

Indeed, comparing the two search engines' distributions of the visited domains, we find them to be fairly close. The KL divergence between the click distributions of the two search engines is only 0.92 bits. This number is quite low considering that the entropy of the click distributions for the two search engines are 16.72 and 14.7 bits, respectively for search engine A and B. Although the two search engines are likely to be using different ranking functions and, hence, displaying different results for the same queries, the click distributions are quite similar.

To put the KL divergence value of 0.92 bits in perspective, contrast it against the KL divergence numbers in Table 2. The displayed results of the same search engine from two different time periods already differ by 1.33 bits, we expect the displayed results of two different search engines to diverge even more. Nonetheless, the 0.92 bits is only slightly higher than the 0.76 bits of divergence in that table.

To summarize, our experiments suggest that users do not blindly visit results surfaced by search engines, instead they show preference for the domains they visit. The concentration of search results on fewer domains is accompanied by an increase in click-through rates. Such a trend may suggest that users have intrinsic preferences for certain domains. However, to understand whether this preference constitutes a bias, we need to conduct more careful experiments since domains are likely to be correlated with relevance. In what follows, we will address this concern, and find out to what extent domains can influence perceived relevance of search results, and verify that even after removing confounding factors such as relevance and position bias, there still remains a systematic domain bias.

4. PEPSI/COKE TEST FOR DOMAINS

We are interested in determining if URL influences perceived relevance. We answer this question via an experiment similar in spirit to the Pepsi/Coke taste test. In our experiment, the products under question correspond to the snippets[3] shown to the user. In the taste test analogy, we are interested in whether simply labeling a product "Pepsi" or "Coke" can make a product taste better.

We measure a user's preference under three different conditions: (1) only the snippets are shown, i.e., URLs are hidden, (2) the snippet and true URLs are shown and (3) the snippet and swapped URLs are shown. The first test is a blind taste test that establishes the baseline. An example is given in Figure 4. The second gives the true labels and the third labels "Coke" as "Pepsi" and vice versa. An example of the second and third experimental conditions is given in Figure 5.

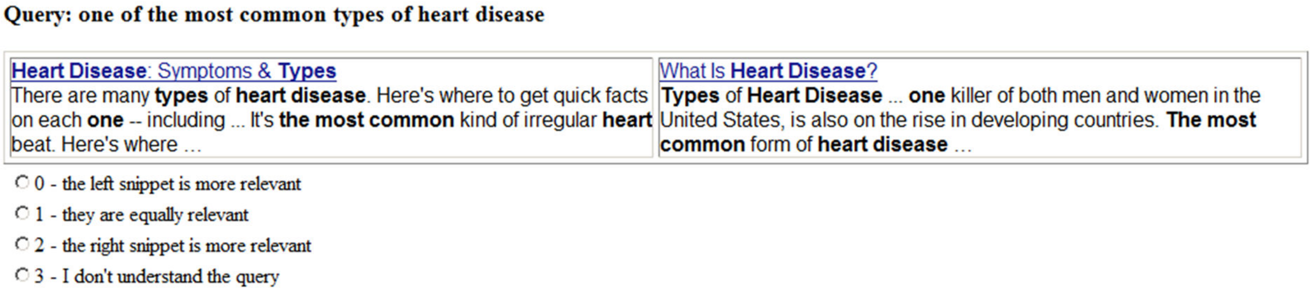
In our experiments, we present these three modes to different human judges and ask them to choose the result with higher relevance. This step is done by creating human intelligence tasks (HITs) on the Amazon Mechanical Turk platform. We describe the details next.

4.1 Setup

We obtain human judgments of the relevance of about 30 URLs each for $14K$ queries sampled from the search log of a commercial search engine. We select queries for which at least two URLs from different domains are judged to be equally and highly relevant to the query. This selection step effectively removes navigational queries for which domains are unlikely to introduce a bias to the perceived relevance of the URLs. Next, we sort the domains by popularity as measured by the frequency with which they appear in the judged URLs. We keep ⟨query, URL1, URL2⟩ tuples for which URL1 belongs to one of the top 50 most popular domains while URL2 belongs to a domain outside of the top 200 most popular domains. This helps to selects tuples for which both URLs are considered equally relevant by a human expert, but one URL belongs to a highly recognizable domain while the other belongs to a more obscure domain. Finally, we sample $1K$ instances from the tuples for which we have successfully obtained snippets for both URLs. The snippets are obtained from a major commercial search engine and anonymized algorithmically based on a set of handcrafted rules so that the content of snippet does not reveal the domain it comes from. This is important as we subsequently paired each snippet with both URLs, and anonymization is needed to avoid creating confusion to the users when a snippet is paired with a different URL.

Using this dataset, we generate HITs to verify the existence of domain bias. Each HIT requires the worker to decide whether one snippet or the other is more relevant to the query. To reduce the effect of presentation bias, we present the two snippets side-by-side, and randomly flip the ordering of the snippets. To mimic the conditions of a search engine,

[3] A snippet is the short summary of a page presented to the user by the search engine. It does not include the URL in our definition.



Query: one of the most common types of heart disease

Heart Disease: Symptoms & **Types** There are many **types** of **heart disease**. Here's where to get quick facts on each **one** -- including ... It's **the most common** kind of irregular **heart** beat. Here's where ...	What Is **Heart Disease**? **Types** of **Heart Disease** ... **one** killer of both men and women in the United States, is also on the rise in developing countries. **The most common** form of **heart disease** ...

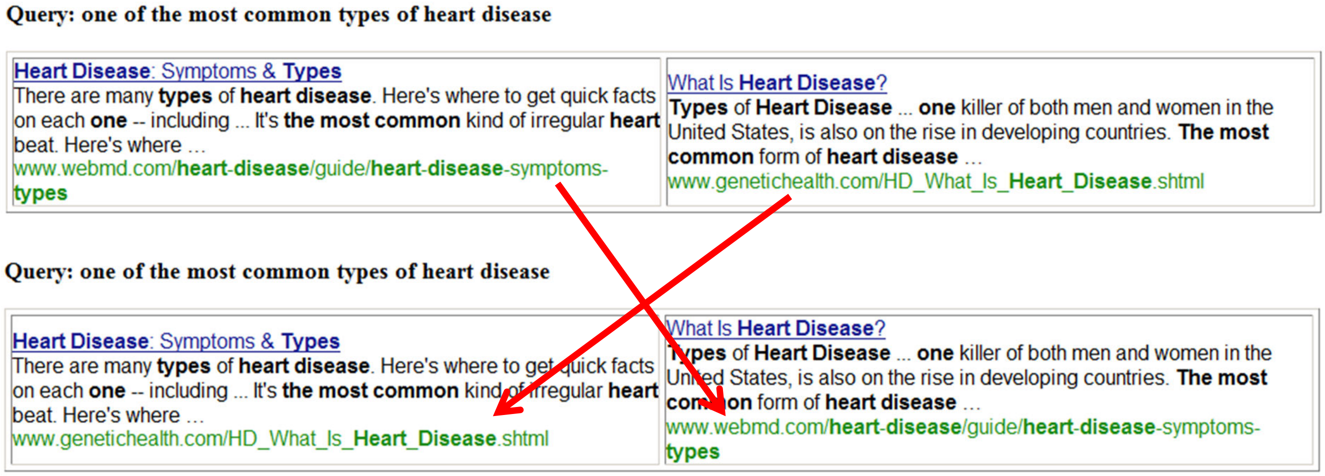
○ 0 - the left snippet is more relevant

○ 1 - they are equally relevant

○ 2 - the right snippet is more relevant

○ 3 - I don't understand the query

Figure 4: The design of the HIT for Mechanical Turks under the first condition—hidden URLs.



Query: one of the most common types of heart disease

Heart Disease: Symptoms & **Types** There are many **types** of **heart disease**. Here's where to get quick facts on each **one** -- including ... It's **the most common** kind of irregular **heart** beat. Here's where ... www.webmd.com/**heart-disease**/guide/**heart-disease**-symptoms-**types**	What Is **Heart Disease**? **Types** of **Heart Disease** ... **one** killer of both men and women in the United States, is also on the rise in developing countries. **The most common** form of **heart disease** ... www.genetichealth.com/HD_What_Is_**Heart**_**Disease**.shtml

Query: one of the most common types of heart disease

Heart Disease: Symptoms & **Types** There are many **types** of **heart disease**. Here's where to get quick facts on each **one** -- including ... It's **the most common** kind of irregular **heart** beat. Here's where ... www.genetichealth.com/HD_What_Is_**Heart**_**Disease**.shtml	What Is **Heart Disease**? **Types** of **Heart Disease** ... **one** killer of both men and women in the United States, is also on the rise in developing countries. **The most common** form of **heart disease** ... www.webmd.com/**heart-disease**/guide/**heart-disease**-symptoms-**types**

Figure 5: The second and third experimental conditions—pairing URLs with snippets. The pairing above corresponds to the correct labeling of the snippet with the URL. The one below swaps the two URLs.

we format the snippets and the URLs in exactly the same manner as a search engine would, together with in-context highlighting. The worker is given four choices: "the left snippet is more relevant", "they are equally relevant", "the right snippet is more relevant", and "I don't understand the query". For each instance ⟨query, URL1, URL2⟩, we generated three different types of tasks corresponding to different experimental conditions, as discussed before. An illustration of the HIT interface is given in Figure 4.

To root out workers who may randomly select answers, we introduce and scatter honeypots into the tasks, and exclude in our results the judgments provided by any workers who have failed the honeypot tests (which is about 10% in the received results). Each instance for each of the experimental conditions is repeated six times, three each for the two different ordering of the snippets.

4.2 Results

For each pair of results (R_1, R_2) presented to the worker i, we assign a rating $q^{(i)}(R_1 : R_2) \in \{1, 0, -1\}$ to R_1 according to the worker's response. The rating indicates whether the worker thinks R_1 is more (1), equally (0), or less (-1) relevant than R_2 for the given query. Averaging over the ratings from the six trials for each of the experimental conditions, we obtain an overall rating $q(R_1 : R_2) \in [-1, 1]$ for each pair of results, with the sign of q indicating the preferences of the workers. We also compute the standard deviation of the ratings and use it to compute confidence intervals of the ratings.

We write a result R as sd if it consists of the snippet s and the URL with domain d, or s if the URL is not shown to the worker. By the three types of tasks we designed, for each pair $(R_1 = s_1d_1, R_2 = s_2d_2)$, we obtain three ratings $q_0 = q(s_1 : s_2)$, $q_1 = q(s_1d_1 : s_2d_2)$, and $q_2 = q(s_1d_2 : s_2d_1)$. We will use q_0 as the baseline and q_1, q_2 to verify to what extent URL influences preference.

If there is no domain bias, then the sign of q_1 and q_2 should be the same as that of q_0's, indicating that the user has the same preference regardless of whether the URL is presented. On the other hand, if $q_1 > 0$ but $q_2 < 0$, it means that users prefer both s_1d_1 to s_2d_2 and s_2d_1 to s_1d_2. This indicates that the user follows the domain d_1 in his preference. Similarly $q_1 < 0$ and $q_2 > 0$ indicates that d_2 is preferred.

Consider the example presented in Figures 4 and 5. When the URLs are not presented, users prefer the *right* snippet. However, when the URLs are presented correctly, they change their preference to the *left* snippet. When the URLs are swapped, their preference flips once again to the *right* snippet. In both the second and third conditions, their preference follows `webmd`. This provides strong evidence that `www.webmd.com` is preferred to `www.genetichealth.com`.

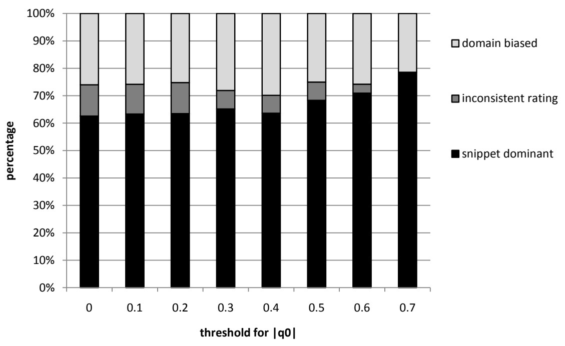


Figure 6: Distribution of three preference patterns with different minimum value of $|q_0|$.

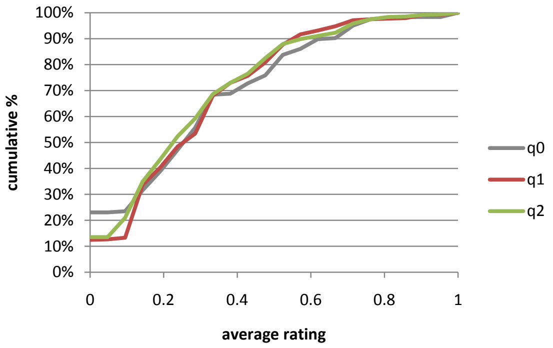


Figure 7: Cumulative distribution of user ratings.

We use this intuition to consider how user preferences are influenced by domains. To do so, we focus on only the ratings for which the workers are "confidently" positive or negative, i.e., we consider only the ratings whose 70% confidence interval is entirely positive or entirely negative. For each pair, according to the sign of q_0, q_1, q_2, we distinguish three cases

- **Snippet dominant.** q_0, q_1, q_2 all have the same sign. In this case, user preferences follow the snippet.
- **Domain biased.** q_1 and q_2 have opposite sign. In this case, user preferences follow the domain.
- **Inconsistent ratings.** q_1 and q_2 have the same sign but opposite to q_0's. This is an inconsistent outcome that cannot be explained by either the snippet or the domain. Such inconsistency is likely due to randomness in human judgments.

Figure 6 shows the distribution of the three cases for different minimum values of $|q_0|$ (non-inclusive). For example, the distribution of cases for the case of $|q_0| = 0.1$ includes all cases for which $|q_0| > 0.1$. As we can see from the graph, a majority of the cases are dominated by the snippet. This is as expected as the snippet contains rich contextual information to help users determine its relevance. However, we see that in a substantial fraction (about 25%) of the cases, user preferences are driven by domains. More importantly, domain bias persists for different values of $|q_0|$. That is, for 25% of cases users follow the URL even when there is a large difference between the perceived relevance of snippets in the absence of URLs! On the other hand, the fraction of inconsistent cases diminishes to 0% as the baseline preferences $|q_0|$ increases, providing evidence that the inconsistent cases are due to randomness in human judgments and they happen only when the users do not have strong preferences between the two snippets by themselves.

A reasonable question is whether users react differently to the three different modes. For example, if the snippet itself contains some domain information, when presented with swapped URLs, the user might get confused by the combination and provide inconsistent feedback. Our results suggest that users are not confused. Consider the distribution of ratings for the three different types of tasks. Figure 7 shows the cumulative distribution of the absolute value of the ratings[4]. First, we note that even though the content of the URLs are judged by human experts to be equally relevant to the query, the workers do not rate the snippets to be equally relevant. Further, comparing the distribution of q_0 and q_1 (and likewise q_0 and q_2), we observe a 10% difference in distribution in the ratings region of $(0, 0.1)$. This difference suggests that users are more inclined to prefer one URL to another when they learn of the URL and its domain. Second, comparing the distribution of q_1 and q_2, we notice that the distribution is almost identical as the two lines overlap one another. This suggests that the pairing of the snippets with both the correct URL and the opposite URL does not introduce systematic bias in the ratings, and alleviates the concern of whether pairing a snippet with an incorrect URL will confuse users.

In summary, the results from the experiments on Amazon Mechanical Turk platform show that while the perceived relevance of a URL is primarily determined by the snippet, which we view as an approximation of the relevance of its content, the exact URL contributes substantively to its perceived relevance. We believe the URL influences perceived relevance through its domain. We verify this in the following section.

5. SYSTEMATIC DOMAIN BIAS

Our previous experiment has demonstrated that the perceived relevance of search results can be swayed by domains. But could this phenomenon be query specific, hence hard to predict for each particular query? In this section, we design experiments to show that domain bias is actually consistent across different queries. Further, based on our experimental data, there exists an ordering of the domains that is highly consistent with the outcome of "head-to-head preference" between two domains as exhibited by users.

[4] Since $q(R_1; R_2) = -q(R_2; R_1)$, the distribution is symmetric, and it suffices to show the distribution of the absolute value.

5.1 Methodology

Designing an experiment to single out the influence of domain turns out to be challenging, as we need to carefully factor out relevance and position bias, two well studied factors that may influence user click behavior [3, 6, 7].

Our strategy is to first identify pairs of webpages in which one is clearly preferred to the other by the users after relevance and position bias is controlled for. We then verify that user preferences are strongly correlated with the domains of the pages and they exhibit a consistent bias across queries. Our experiment consists of three steps.

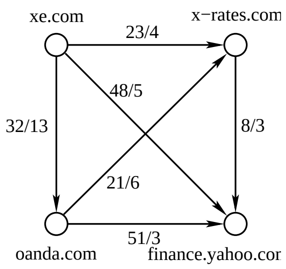
First, we identify pairs of URLs p_1 and p_2 that are deemed to be equally relevant to a query q, denoted by $p_1 \sim_q p_2$. The relevance of the URLs for the query are determined by human judges.

Next, we identify user preferences between two URLs that cannot be explained by position bias. For each pair of equally relevant URLs, we examine the search logs for instances where both appeared in the search results. We then count the number of times p_1 preceding p_2 and vice versa. We also count the number of clicks both URLs received. We say that p_1 is preferred to p_2 under q, $p_1 \rightarrow_q p_2$, if p_1 receives more clicks *and* p_2 appears before p_1 *more* often than p_1 before p_2. The latter requirement is there to ensure that the preference is not explicable by position bias.

Finally, we aggregate these preferences at the domain level and determine if the users exhibit a systematic bias based on hypothesis testing. This is a complex step that involves a number of sub-steps. First, we construct a *domain preference graph* based on user preferences from the last step. The domain preference graph, $G = \langle V, E \rangle$, is a unweighted directed multi-graph. The nodes V in the graph represent domains. For each preference $p_1 \rightarrow_q p_2$ we add a directed edge from the domain of p_1 to the domain of p_2 (we ignore the pair if p_1, p_2 are from the same domain). The graph can be viewed as a summary of the preference the users exhibit over the domain.

We show an example taken from a domain preference graph constructed in our experiments in Figure 8. The data behind this graph is discussed further in the next section. The nodes in this sub-graph are domains related to exchange rates. For presentation, we drew only a single edge between each pair of domains (u, v). The two numbers on the edge, x/y, represent the number of the edges that go with the indicated direction (x) and those that go backwards (y). Recall that this graph is actually an unweighted multi-graph.

An important statistic that we compute over the domain preference graph G is the *maximum agreement rate*, $\mathrm{A}(G)$. Given a linear order L over the nodes V, $(v_1 > v_2 > \cdots > v_n)$, we say that an edge $e = (v_i, v_j)$ *agrees* with the order, $L \Rightarrow e$, if $v_i > v_j$ according to L. The *agreement rate* between graph G and order L, $\mathrm{A}(G, L)$, is defined as the fraction of edges E in G that agrees with L, i.e., $|\{e \mid L \Rightarrow e\}|/|E|$. The maximum agreement rate, $\mathrm{A}(G)$, is defined as the agreement rate achieved by the best linear order, $\mathrm{A}(G) = \max_L \mathrm{A}(G, L)$. As an example, consider the sub-graph in Figure 8. The best linear order over the nodes is (`xe.com` > `oanda.com` > `x-rates.com` > `finance.yahoo.com`). Under this order, $\mathrm{A}(G, L) = (32+23+48+21+51+8)/(32+13+23+4+48+5+21+6+51+3+8+3) \approx 0.84$, the ratio between the number of forward edges and the total number of edges.



queries
foreign currency converter
currency exchange rates
foreign exchange rates
foreign money converter
euro currency converter
currency rates
currency converter
conversion dollars
convert to us dollars
convert currency
world currency rates

Figure 8: A sub-graph of the domain preference graph. In the left figure, each node corresponds to a domain, and each (super)edge represents the set of multi-edges between the two nodes. The two numbers on each super-edge represent the number of forward and backward multi-edges with respect to the direction of the arrow. For example, there are 32 multi-edges from `xe.com` to `oanda.com` and 13 multi-edges from `oanda.com` to `xe.com`. On the right is the list of top 10 queries that contribute to the multi-edges of the graph.

But does the value 0.84 confirm the existence of a systematic bias? To answer, we use statistical hypothesis testing. Our null hypothesis, H_0, is that there is *no* systematic bias. If so, the observed preference relationship would have been arisen from a random process, and that for each preference $p_1 \rightarrow_q p_2$, we would have equally likely observe $p_2 \rightarrow_q p_1$, since the preference is random. Hence, our statistical experiment consists of the following. For each preference relationship, we flip a fair coin to decide whether p_1 is preferred to p_2 or vice versa. We then construct the corresponding domain preference graph G', and compute $\mathrm{A}(G')$. If the observed value of $\mathrm{A}(G)$ is significantly larger than the mean value of $\mathrm{A}(G')$, we reject H_0, thus confirming the existence of domain preference. Note that one cannot simply confirm the existence of domain preference by the maximum agreement rate alone. This is because for very sparse graphs, $\mathrm{A}(\cdot)$ will be close to one regardless of the direction of the edges. Hence, it is important to consider the statistical hypothesis testing explained above.

There are practical reasons we choose to test according to $\mathrm{A}(G)$. If we are to assign a number to each domain as a measure for the domain preference, it necessarily imposes a linear order on the domains. By definition, $\mathrm{A}(G)$ is the maximum agreement of any linear order with the preference graph. Therefore, it represents the best we can achieve if we are to preserve the preference order faithfully.

To close this section, we note that computing $\mathrm{A}(G)$ exactly is equivalent to solving the *minimum feedback-arc set*, an NP-hard problem. In our experiments, we use a local search algorithm that starts from an arbitrary linear order and swaps two vertices until no improvement can be made. This is repeated many times and the best linear order is selected. While there is no direct performance guarantee on the algorithm, we found that it works well as it typically finds solution with maximum agreement rate close to an upper-bound estimated by summing over all pairs of nodes v_i and v_j the larger of the size of the two sets of edges $|(v_i, v_j)|$ and $|(v_j, v_i)|$. The value is a valid upper bound

	G_0	G_q	G_p	$G_{q,p}$
`# of vertices`	60	287	282	1020
`# of edges`	33	308	575	7519

Table 3: The size of preference graphs.

since no linear order can agree with both (v_i, v_j) and (v_j, v_i) simultaneously.

5.2 Results

To instantiate the framework, for step 1, we obtain human judgment for about $2K$ queries (mostly informational queries) and $770K$ pairs of URLs, each judged by a panel of 11 judges. We keep only those pairs for which at least 8 out of 11 judges deemed the two URLs to be equally relevant to the query, resulting in about $130K$ pairs. For step 2, we examine 6 months of search logs from July 2010 to December 2010 and keep the preference relationship in cases where there are at least 5 clicks in total for both results. We then construct the domain preference graph G_0. Unfortunately, due to index churn between the time when the URLs are judged and the collection of the log data, we found very few pairs of the judged URLs appearing together in the log, and the number of directed edges is further reduced due to the stringent requirement in step 2 that corrects for position bias, giving rise to a very sparse graph. The graph is unsuitable for the hypothesis testing framework as most random instantiation of it will be perfectly consistent with some linear ordering of the domains.

To remedy this situation, we relax the definition of equivalent pairs in the first step. We consider three approaches for each pair $p_1 \sim_q p_2$. Under *query relaxation*, we include a pair $p_1 \sim_{q'} p_2$ if q' is a super-string of q. Under *page relaxation*, we include a pair $p'_1 \sim_q p'_2$ if pages p'_1 and p'_2 are from the same domain as p_1 and p_2 respectively. Under the *query-page relaxation*, we allow both query and page relaxations. The domain preference graphs based on these three relaxations are denoted G_q, G_p, and $G_{q,p}$ respectively. We summarize the statistics of all four graphs in Table 3.

While it is possible that the relaxation we performed may introduce noise in the results, by requiring that both p_1 and p_2 have surfaced in response to a query, and that the user clicks on at least one of the results, the drift in query intent is limited. Hence the relevance judgments still apply to the expanded set of results. This is demonstrated by the set of queries related to *exchange* and *currency* that appeared in Figure 8. For example, even though "microsoft exchange" is a super-string of "exchange", it was not included because the domains surfaced do not match the exchange currency domains in the human judgment data set. To further ensure the safety of this relaxation step, we also manually check a random sample of the data and find that the relaxation does indeed produce coherent sets of queries and results.

The values of $\mathrm{A}(\cdot)$ for preference graphs G_q, G_p, and $G_{q,p}$ are shown in Table 4, along with the sample mean and confidence interval at $p = 0.99$ under the null hypothesis H_0. For all three graphs, the value $\mathrm{A}(\cdot)$ for the actual graph lies outside the confidence interval of the null hypothesis, hence we can reject the null hypothesis and confirm that users do indeed exhibit a systematic and consistent bias over domains.

	G_q	G_p	$G_{q,p}$
$\mathrm{A}(\cdot)$	0.90	0.85	0.76
$\mathrm{A}(\cdot)$ under H_0	0.83 ± 0.008	0.71 ± 0.007	0.60 ± 0.005

Table 4: The maximum agreement rate $\mathrm{A}(\cdot)$ on graph G_q, G_p, $G_{q,p}$ and under the null hypothesis that randomly flips the direction of the preference, with its 0.99 confidence interval.

6. DISCUSSION AND FUTURE WORK

The phenomenon that Internet users favor certain domains over others in their visits is not a new discovery. Indeed, past work has recognized the importance of domains in web search [10]. One explanation of why this happens is that documents belonging to a domain are typically written by the same author, as in the case of a blog, or are subject to the same quality control, as in the case of a wiki or a news organization, and therefore good documents are often clustered at the domain level. Our experiment in Section 3 confirms that users indeed have discovered the good domains, and their visits are increasingly concentrated on these domains.

The new phenomenon discovered in this paper is that user preferences of certain domains to others is beyond what can be explained due to relevance, and creates a bias similar in spirit to position bias [11] and snippet bias [23]. The bias manifests itself as leading a user to perceive the same document as being more relevant when it is attached to a more reputable domain than a less reputable one. Its existence is established beyond reasonable doubt through a series of carefully controlled experiments in Sections 4 and 5.

Why is domain bias an important concept and how does it influence search today? First, it has important consequences for click prediction, a central problem for both web search and sponsored search. Many click models have been proposed in the web literature over the past few years [3, 6, 7, 9]. While these models differ in how they capture user behavior, a common theme is that they focus on three factors that influence how users click—the user queries, the positions of the results, and the relevance of the results. The existence of domain bias implies that the precision of these models can be improved, and the design of click models should be revisited in light of the findings in this paper.

Second, domain bias has important consequences on learning relevance from clicks, the dual problem to click prediction. The web community has long recognized the importance of clicks as a source of signal for learning relevance, and there are many studies on how to learn relevance in the presence of position bias [2, 7, 11]. As domain bias becomes stronger, we need new learning algorithms that can account for domain bias. This is a challenging problem as domain bias exists partly due to difference in relevance across different domains, and therefore it cannot be easily teased out as a component separate from relevance. Further, users may exhibit different bias depending on the class of queries. For example, while users may strongly prefer `wikipedia.org` for queries about world geography, users may prefer `amazon.com` for queries about digital cameras. Whether we should consider bias at a query level or at a category level (and if so, which degree of categorization) will influence the success of the learning algorithm.

Finally, domain bias also affects existing approaches for classifying queries into navigational vs. informational ones. One common approach for determining whether a query is navigational is based on the entropy of its clicks. As domain bias becomes stronger, user visits are concentrated on fewer domains, even for informational queries. Algorithms for distinguishing between informational and navigational queries may have to be revisited in the presence of domain bias.

In view of the important consequences of domain bias, how does one go about measuring this bias? This is a fundamental and challenging question to which we only have a partial answer. The main obstacle to successfully measuring domain bias is the need to control for other factors that may lead a user to prefer one domain to another, chief among which is relevance, although other forms of confounding bias such as position bias also play a role. The experiment in Section 5 offers our best effort in isolating domain bias in a controlled setting. We believe it is a sound approach to both establishing and estimating domain bias. Nonetheless, it only constitutes a partial answer to the measurement question, as the methodology cannot be easily scaled up due to the need for a large quantity of human labels. Our limited data-set has forced us to use various heuristics to expand our coverage of domains; to scale to all domains is out of reach today. We believe that as user visits become increasingly concentrated on certain domains, domain bias will become an even more important issue, and measuring domain bias will be an important future research topic. Progress in this area will also have important implications on how to measure other forms of bias in web search.

Domain bias has led users to concentrate their web visits on fewer and fewer domains. It is debatable whether this trend is conducive to the health and growth of the web in the long run. Will users be better off if only a handful of reputable domains remain? We leave it as a tantalizing question for the reader.

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